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Stress Detection through Compound Facial Expressions Using Neural Networks

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Abstract: Human face is the most dynamic part of the body that conveys information about the instant emotions. Facial expression analysis starts from early 1900s where later on scientists identify the six basic facial expressions as Anger, Disgust, Fear, Happiness, Sadness, Surprise and Neutral with the pioneering studies of psychologists. In the last decades, the acceleration in artificial intelligence and computer vision research makes it possible to automatically detect facial expressions through images. Furthermore, micro expressions, muscle movements and compound facial expressions; that are the combinations of the basic expressions can be also analyzed with computer vision algorithms. The main motivation in automatic facial expression analysis is to support human-computer. Furthermore, facial expression analysis can be a driver for automatic emotion analysis. In this study, we propose a novel method to detect stress indicators on the frontal face images. The detection procedure is based on compound facial expression analysis. 49 couples of 6 basic facial expressions where one is dominating, and the other is the complementary expression are employed. iCV-MEFED facial expression dataset is used in the experiments where video and image samples are provided for every compound facial expression class. The training and testing of compound facial expressions are done using a deep neural network. The robust representations of faces are achieved using a fusion method that combines deep texture features and the action units on the face. Then, through the appropriate grouping of the compound expressions, the system can detect the signs of stress. The proposed approach obtains encouraging results, and it is open to further improvements.

Keywords: Facial expression analysis, Stress detection, Emotion analysis, Compound expressions, Machine learning.

Introduction

Face and facial expressions involve significant information about the instant emotional states of humans. Starting from early 1900s, even before, the psychologists have observed human and animal facial expressions and attempted to categorize them. There are categorizations that are accepted by the community and the research studies are following. Together with the advancements in artificial intelligence and computer vision fields, implementing a robust facial expression analyzer on real time became possible. Automatic facial expression analysis also supports human computer interaction and is utmost important in this sense. Furthermore, besides the automatic computer vision systems classifying the facial expressions, there are approaches that classifies facial expressions based on the dimensions of valence (positive-negative) and arousal (activation level), representing emotional intensity and affective states. In summary, we can summarize the facial expression analysis directions as follows (Sajjad et al., 2023):

- Basic Emotions Classification
  Basic emotional categories such as happiness, sadness, anger, fear, surprise, disgust, and neutral expressions
- Compound Emotions Classification
  Classifies facial expressions into compound or complex emotional states that combine basic emotions, such as happy-sad, angry-surprised, or fear-disgust
- Action Unit (AU) Classification
  Typically uses machine learning algorithms to detect and classify AUs from facial landmarks or image patches, facilitating detailed analysis of facial expressions.
- Valence-Arousal Classification
  Classifies facial expressions based on the dimensions of valence (positive-negative) and arousal (activation level), representing emotional intensity and affective states.
- Micro-Expression Classification
  Micro-Expression Classification focuses on detecting and classifying subtle and rapid facial expressions known as micro-expressions which occur within fractions of a second and often reveal concealed emotions. Utilizes high-speed imaging, motion analysis techniques, and specialized classifiers to capture and classify micro-expressions accurately.

The above-mentioned categorizations can be utilized to build applications on top such as diagnosis of disorders, security or learning. Currently there are active research studies to bring a robust solution to compound and micro expression analysis.

Literature Summary

Recognizing facial expressions by computers presents a formidable challenge due to various factors, including the diverse physiognomy of individual faces, head poses, and lighting conditions (Nonis, Dagnes, Marcolin, & Vezzetti, 2019). This task becomes even more intricate when dealing with compound emotions or facial expressions, which adds complexity to an already demanding analysis. A significant hurdle in human emotion recognition lies in the scarcity of robust and well-labeled datasets pertaining to human emotions (Martinez, & Valstar, 2016). While most analyses focus on the seven primary human emotions - sadness, disgust, anger, happiness, surprise, fear, and contempt (Ekman, 1992) - recent research efforts have been directed towards advancing the analysis of compound facial expressions and emotions (Yu et al., 2018; Hu et al., 2017; Guo et al., 2017; Du & Martinez, 2022), driven by advancements in tools for compound human emotion analysis (Loob et al., 2017).

Psychological studies have revealed that different regions of the face convey distinct emotional cues through facial expressions (Levi & Hassner, 2015; Zhao et al., 2016; Grobova et al., 2017). Further investigations suggest that certain facial regions carry more emotional information than others (Lusi et al., 2017). For instance, the eyes and eyebrows are primary conveyors of emotions like fear and anger, whereas expressions of happiness and disgust are predominantly exhibited through the mouth region. The expression of surprise may involve both the mouth and the eyes/eyebrows regions (Kulkarni et al., 2018)

Although much research has focused on the six basic human emotions as defined by Ekman and Friesen - fear, anger, disgust, sadness, surprise, and happiness (Ekman & Friesen, 1971) - psychological studies indicate that emotions extend beyond these basic categories, influenced by factors such as mental states, interpersonal relationships, and cultural backgrounds (Keltner et al., 2019; Haamer et al., 2017). Noroozi et al. (Noroozi et al., 2017) extensively discuss compound human emotions, which combine two basic emotions with one acting as dominant and the other complementary. The complexity of compound human emotions poses significant challenges in recognition and classification, as the fusion of two basic emotions amplifies the intricacy of emotional states.

Automatic stress detection from facial images is a burgeoning area of research aiming to develop computational methods for accurately identifying stress levels based on facial expressions. The detection of stress from facial images holds promise for various applications, including healthcare, human-computer interaction, and psychological research.

Several studies have investigated different approaches and techniques for automatic stress detection from facial images. One common approach involves feature extraction from facial images using techniques such as facial landmark detection, facial action unit analysis, and texture analysis. These features capture subtle changes in facial expressions associated with stress, such as furrowed brows, tense lips, or widened eyes. Machine learning algorithms, including support vector machines (SVM), convolutional neural networks (CNN), and deep learning architectures, are commonly employed for stress classification. These algorithms are trained on labeled datasets of facial images annotated with stress levels to learn patterns and relationships between facial features and stress states.

For example, some studies revealed promising results concerning methods using machine learning and deep learning for facial parameters such as facial expression (Dinges et al., 2005), semi- or/and non-voluntary facial features (Giannakakis et al., 2017), action units (Giannakakis et al., 2020) as well as integrating basic emotion classes (Zhang et al., 2019). However, no studies have been conducted to examine the integration of compound emotions in the detection of stress.

Several challenges exist in automatic stress detection from facial images, including variability in facial expressions across individuals, the subjective nature of stress, and the need for large and diverse datasets for training robust models. Additionally, addressing ethical considerations, such as privacy concerns and potential biases in algorithmic predictions, is essential in the development and deployment of stress detection systems. In this respect, the current study is unique; it is the first endeavor to scrutinize stress detection through compound facial expressions using neural networks.

The paper proposes a valence-arousal classification-based approach in order to detect the signs of stress automatically from the frontal face images. The main contribution of the paper is to explore the mapping between the compound facial expressions and the presence of stress signs accordingly. There are many datasets including compound facial expressions. In our study, we employ iCV-MEFED dataset that is the richest compound expression dataset including the 50 compound expression classes where dominant and complementary combinations of the six basic expressions are used (Guo et al., 2018).

Stress Detection through Compound Facial Expressions

The proposed system consists of two main blocks. The first part is the compound expression analyzer proposed by Jiddah and Yurtkan (2023), and the second part is the proposed stress detection mapping under the supervision of our expert psychologist. Convolutional neural networks (CNNs) and Long-Short Term Memory (LSTM) networks are employed.

iCV-MEFED Dataset

The iCV-MEFED dataset, developed and compiled by Guo et al. (2018), represents a unique collection of human compound emotions. It addresses the limitations of existing publicly available datasets by offering a comprehensive range of 50 fine-grained emotional classes. This dataset is pioneering in its scope, containing 31,250 facial images sourced from 125 subjects, ensuring a balanced representation of genders and diverse ethnic backgrounds, with subjects aged between 18 and 37 years. Notably, all images in the iCV-MEFED dataset are captured under controlled conditions to minimize data noise, including factors like background interference, varying illumination, and head pose discrepancies. Such efforts are crucial to mitigate biases that may affect the analysis and classification outcomes of the images (Clark et al., 2020). Each subject in the dataset is guided by a trained psychologist to enact five samples of each of the 50 emotions, ensuring accurate expression of the complex emotional spectrum. The exhaustive list of 50 emotional classes captured in the dataset is detailed in Table 1. Figure 1 shows example faces from the dataset.

Compound Facial Expression Recognizer

In the hybrid recurrent neural network (RNN) method, the classification model's input data comprises AU (Action Unit) feature data extracted from the dataset. Following AU feature extraction, each image in the dataset is depicted by a 35-feature vector, comprising 18 AU presence features and 17 AU intensity features. All images in the dataset undergo AU feature extraction and are subsequently labeled based on their emotion class, facilitating classification. Therefore, the input data dimension for this approach is a 35×1 feature vector.

Figure 1. Examples from icv-mefed dataset.

CNN-LSTM represents a type of deep learning architecture that amalgamates two distinct deep learning networks, thereby creating a hybrid network that harnesses the computational benefits of both networks (Wang et al., 2020). In this framework, CNN-LSTM utilizes the initial layers of the CNN network to perform feature extraction from the input data, which, in our experimental setup, comprises the AU data feature vector. Subsequently, the extracted features are forwarded to the LSTM network for classification and prediction. LSTM networks offer a notable advantage over generic recurrent neural networks due to their utilization of memory blocks, facilitating expedited learning processes (Amin et al., 2019). CNN-LSTM networks have demonstrated efficacy in executing deep learning tasks efficiently, and our proposed methodology aims to capitalize on the availability of a series of five emotion images in each class for every subject in the iCV-MEFED dataset.

Table 1. Compound facial expression classes of icv-mefed Dataset (Guo, et al., 2018).

	Angry	**Contempt**	**Disgust**	**Fear**	**Happy**	**Sadness**	**Surprise**
Angry	**Angry**	Contempt angry	Disgust angry	Fear angry	Happy angry	Sadness angry	surprise angry
Contempt	Angry contempt	**Contempt**	Disgust contempt	Fear contempt	Happy contempt	Sadness contempt	Surprise contempt
Disgust	Angry disgust	Contempt disgust	**Disgust**	Fear disgust	Happy disgust	Sadness disgust	Surprise disgust
Fear	Angry fear	Contempt fear	Disgust fear	**Fear**	Happy fear	Sadness fear	Surprise fear
Happy	Angry fear	Contempt happy	Disgust happy	Fear happy	**Happy**	Sadness happy	Surprise happy
Sadness	Angry sadness	Contempt sadness	Disgust sadness	Fear sadness	Happy sadness	**Sadness**	Surprise sadness
Surprise	Angry surprise	Contempt surprise	Disgust surprise	Fear surprise	Happy surprise	Sadness surprise	**Surprise**

The implemented CNN-LSTM model in this study is structured with a total of 12 layers, each layer configured as follows: an input layer, three max-pooling layers, five convolutional hidden layers, one LSTM layer, one dense layer, one dropout layer, and an output layer. The max-pooling layers serve to condense the feature dimensions through feature summarization, aiding in convolutional layer padding. The LSTM layer is integrated into the architecture post-feature summarization by the last pooling layer, resulting in a feature map comprising the most pertinent features for classification. All input data are vectorized into a 35 × 1 (35, 1) input dimension for our model. The convolutional layers engage in feature extraction utilizing the ReLU activation function, while the batch size is set at 64. Additionally, the model employs the Adam optimizer with a learning rate of 0.001 and a categorical loss function.

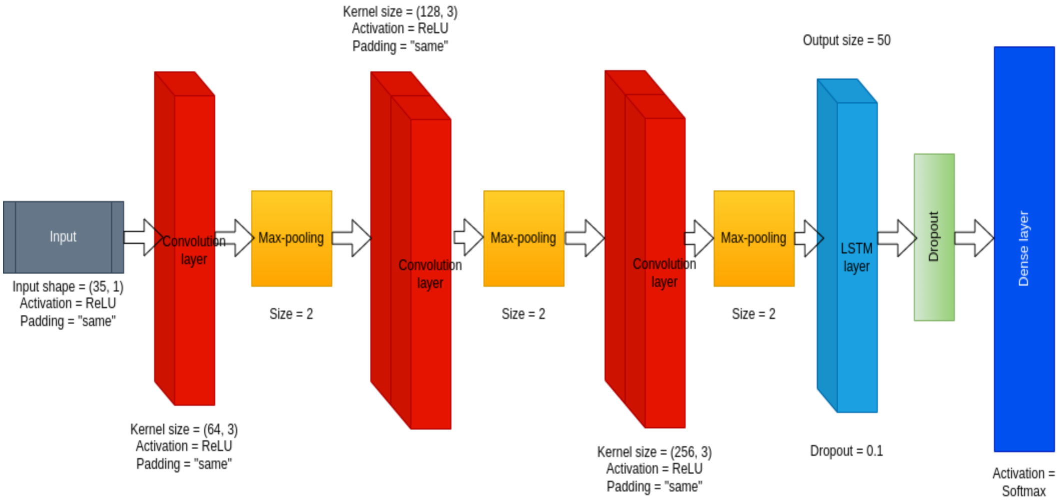

Figure 2. CNN-LSTM hybrid neural network model used.

Stress Detection through Facial Expressions

The signs of stress can be analyzed through facial information. In our study, we concentrate on the standardized basic facial expressions and their compound versions in order to explore the stress indicators. Together with our expert psychologist's supervision, we have found that the marked compound facial expression classes in Table 2 are carrying information about the stress. Thus, the neural networks are re-trained according to the Table 2, where marked stress related compound expressions are treated as positive class, and the unmarked classes are treated as negative class. In total, 20 classes are selected as stress indicators.

Table 1. Stress indicator compound facial expression classes excluding contempt compound expressions of icv-mefed dataset where boxed classes are positive classes.

	Angry	**Contempt**	**Disgust**	**Fear**	**Happy**	**Sadness**	**Surprise**
Angry	**Angry**	Contempt angry	Disgust angry	Fear angry	Happy angry	Sadness angry	surprise angry
Contempt	Angry contempt	**Contempt**	Disgust contempt	Fear contempt	Happy contempt	Sadness contempt	Surprise contempt
Disgust	Angry disgust	Contempt disgust	**Disgust**	Fear disgust	Happy disgust	Sadness disgust	Surprise disgust
Fear	Angry fear	Contempt fear	Disgust fear	**Fear**	Happy fear	Sadness fear	Surprise fear
Happy	Angry fear	Contempt happy	Disgust happy	Fear happy	**Happy**	Sadness happy	Surprise happy
Sadness	Angry sadness	Contempt sadness	Disgust sadness	Fear sadness	Happy sadness	**Sadness**	Surprise sadness
Surprise	Angry surprise	Contempt surprise	Disgust surprise	Fear surprise	Happy surprise	Sadness surprise	**Surprise**

Since the review of the literature revealed no studies exploring the relationship between compound emotions and stress, the compound emotions of emotional stress are grouped according to the basic emotions that the expression of stress has been linked to. Stress has been linked with negative affect and reflected in the emotions of sadness, fear, anger, and disgust (Das & Yamada, 2013; Lerner et al., & Taylor, 2007; Lazarus, 2006; Zautra, 2006). Thus, among the seven basic emotions, emotional stress is grouped according to disgust, sadness, anger, and fear and their compounds as shown in Table 1. In the face of stressful events, positive feelings (i.e., happiness) and negative emotions (i.e., sadness) have been found to have an inverse relationship (Zautra et al., 2010). In this regard, compound emotions involving positive and negative emotions have not been considered for examination.

Table 2. Stress indicator compound facial expression classes including contempt compound expressions of icv-mefed dataset where boxed classes are positive classes.

	Angry	**Contempt**	**Disgust**	**Fear**	**Happy**	**Sadness**	**Surprise**
Angry	**Angry**	Contempt angry	Disgust angry	Fear angry	Happy angry	Sadness angry	surprise angry
Contempt	Angry contempt	**Contempt**	Disgust contempt	Fear contempt	Happy contempt	Sadness contempt	Surprise contempt
Disgust	Angry disgust	Contempt disgust	**Disgust**	Fear disgust	Happy disgust	Sadness disgust	Surprise disgust
Fear	Angry fear	Contempt fear	Disgust fear	**Fear**	Happy fear	Sadness fear	Surprise fear
Happy	Angry fear	Contempt happy	Disgust happy	Fear happy	**Happy**	Sadness happy	Surprise happy
Sadness	Angry sadness	Contempt sadness	Disgust sadness	Fear sadness	Happy sadness	**Sadness**	Surprise sadness
Surprise	Angry surprise	Contempt surprise	Disgust surprise	Fear surprise	Happy surprise	Sadness surprise	**Surprise**

Analysis of Contempt Expression

Despite contempt being a form of negative emotion, it has been the least studied emotion among the basic seven emotions. This, examination of its relationship with stress, has also been found as an underexamined area in literature. This could be originated from the fact that contempt is regarded as a more human-targeted social emotion helping in the regulation of hierarchies (Fischer et al., 2022). The research on contempt and relationships has revealed associations between contempt and a lack of control over the other person (Fischer & Roseman, 2007), breakup-related distress (Heshmati et al., 2017), low competence and self-esteem (Schriber et al.,, 2017) as well as contempt and lower levels of self-reported stress (Crowley, 2013). The associations between contempt and relationships point out a potential relationship between coping and stressful situations. Therefore, an alternate table including the previously classified compound emotions along with; contempt and compound emotions of contempt with disgust, fear, sadness and anger has been created, as shown in Table 2. The average accuracy found in detecting stress was 72.92%, compared to 71.28% in Table 1, which excluded contempt and its compounds with the stress emotions. The slight increase could mean that contempt has a role in the process and regulation of stress.

Results and Discussion

The experiments are completed on iCV-MEFED dataset with 80:20 ratio of testing and validation. 5-fold cross validation method is applied to validate the results. A class that is mapped as a stress indicator is treated as positive class, and others are treated as negative class. The performance metrics of accuracy, precision, sensitivity, specificity and F1-score are used to evaluate the system. The usual classification metrics used are true negative (TN); which is the number of correctly identified negative classes in predictions, true positive (TP); which is the number of correctly identified positive classes in predictions, false negative (FN) this is the number of incorrectly identified negatives in predictions, false positive (FP); this is the number of incorrectly identified positives in the predictions. Formulas related to the performance metrics are listed from equation 1 through equation 5.

Accuracy = (TP+TN)/(TP+TN+FP+FN) (1)
Precision = TP/(TP+FP) (2)
Sensitivity = TP/ (TP+FN) (3)
Specificity = TN/ (TN+FP) (4)
F1 score = 2 * ((Precision * Recall)/ (Precision + Recall)) (5)

Table 3. Performance evaluations of the proposed system based on the positive classes listed in table 1.

Fold	Accuracy	Precision	Sensitivity	Specificity	F1 score
Fold 1	71.33	61.07	30.70	90.68	40.86
Fold 2	70.92	60.77	31.52	90.10	41.51
Fold 3	72.99	75.86	89.86	34.10	82.27
Fold 4	70.68	58.89	30.77	89.74	40.42
Fold 5	70.48	72.67	90.16	29.65	80.48
Average	**71.28**	**66.0**	**55.0**	**67.0**	**57.0**

It can be observed from the Table 3 that the system can recognize the signs of stress automatically with the average accuracy of 72.92 % that is an acceptable rate. Furthermore, the system is more sensitive to signs of stress. Considering the challenges in the problem, the overall performance of the system is acceptable and is open to further improvements. On the other hand, the selection of contempt expression is still a challenge that we found, and then experiments are also accomplished with the compound contempt expressions excluded. In terms of average accuracy, the two approaches are approximately performing in the similar levels. However, from the view of sensitivity, the contempt expression and its compounds bring significant improvements.

The compound facial expression analysis is still a challenging problem of computer vision when considering more compound classes like 50 in total, that are used in our study. The average accuracies are even below 50% in most of the proposed models. Although the robust recognition of compound expressions brings different challenges to resolve, they can form a good basis for psychological analysis through faces, from the aspects of depression, stress and anxiety. The results shown that dominant and complementary expression classes can be a good basis for analyzing the signs of stress.

Table 4. Performance evaluations of the proposed system based on the positive classes listed in table 2.

Fold	Accuracy	Precision	Sensitivity	Specificity	F1 score
Fold 1	73.37	73.63	73.60	73.14	73.61
Fold 2	72.88	73.74	71.64	74.13	72.68
Fold 3	73.01	71.01	74.96	71.17	72.96
Fold 4	73.12	71.62	74.71	71.59	73.13
Fold 5	72.20	70.91	74.25	70.20	72.54
Average	**72.92**	**72.0**	**74.0**	**72.0**	**73.0**

Conclusion

The paper proposes a stress detection system based on compound facial expressions. The challenging problem of detecting the signs of stress through frontal faces is attacked. The proposed system is taking iCV-MEFED dataset as a basis that includes the highest number of compound expression classes in the research studies where there are 50 classes composed of the dominant and complementary combinations of the six basic expressions. An extensive mapping of compound expression classes to stress indication is performed. The computer vision part of the system is employing a hybrid CNN and LSTM neural networks. The system is evaluated on the dataset by applying 5-fold cross validation. The performances of the system reached to 72.92 % accuracy and shown that the proposed methodology achieves encouraging results giving directions to further improvements.

Analysis of Contempt Expression

The system's overall accuracy is beyond 70% and this level of performance is acceptable. Furthermore, the system is open to performance improvements. A possible future work is to employ texture feature extraction techniques like Local Binary Patterns (LBPs) to enhance the facial representations to improve the system's performance. Another similar direction may be the improvements in the deep learning model used. One of the possible future works to adapt is to investigate the compound expression basis for the signs of depression and anxiety. Similar input level and neural network level enhancements are also to be considered for these future directions. Overall, the proposed system forms a basis and opens new directions for further facial analysis based on dominant and complementary facial expressions.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the authors.

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References

Clark, E. A., Kessinger, J. N., Duncan, S. E., Bell, M. A., Lahne, J., Gallagher, D. L., & O'Keefe, S. F. (2020). The facial action coding system for characterization of human affective response to consumer product-based stimuli: a systematic review. *Frontiers in Psychology, 11,* 920

Crowley, J. P. (2013). Attributes of highly contemptuous people. *Western Journal of Communication, 77*(3), 340-360.

Das, S., & Yamada, K. (2013). Evaluating instantaneous psychological stress from emotional composition of a facial expression. *Journal of Advanced Computational Intelligence and Intelligent Informatics, 17*(4), 480-492.

Dinges, D. F., Rider, R. L., Dorrian, J., McGlinchey, E. L., Rogers, N. L., Cizman, Z., Goldenstein, S. K., Vogler, C., Venkataramun, S., & Metaxas, D. N. (2005). Optical computer recognition of facial expressions associated with stress induced by performance demands. *Aviation, Space, And Environmental Medicine*, *76*(6), 172-182.

Du, S., & Martinez, A. M. (2015). Compound facial expressions of emotion: from basic research to clinical applications. *Dialogues in Clinical Neuroscience*, *17*(4), 443-455.

Ekman, P., & Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of Personality and Social Psychology, 17*(2), 124.

Ekman, P. (1992). An argument for basic emotions. *Cognition & Emotion, 6*(3-4), 169-200.

Fischer, A. H., & Roseman, I. J. (2007). Beat them or ban them: the characteristics and social functions of anger and contempt. *Journal of Personality and Social Psychology, 93*(1), 103.

Fischer, A. H., Roseman, I. J., & Giner-Sorolla, R. (2022). Contempt: The emotional rejection of those who are beneath our standards. In *Emotions in culture and everyday life* (pp. 166-182). Routledge.

Giannakakis, G., Pediaditis, M., Manousos, D., Kazantzaki, E., Chiarugi, F., Simos, P. G., Marias, K., & Tsiknakis, M. (2017). Stress and anxiety detection using facial cues from videos. *Biomedical Signal Processing and Control, 31,* 89-101.

Giannakakis, G., Koujan, M. R., Roussos, A., & Marias, K. (2020). Automatic stress detection evaluating models of facial action units. In *2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020)* (pp. 728-733). IEEE.

Grobova, J., Colovic, M., Marjanovic, M., Njegus, A., Demire, H., & Anbarjafari, G. (2017). Automatic hidden sadness detection using micro-expressions. In *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)* (pp. 828-832). IEEE.

Guo, J., Zhou, S., Wu, J., Wan, J., Zhu, X., Lei, Z., & Li, S. Z. (2017). Multi-modality network with visual and geometrical information for micro emotion recognition. In *2017 12th IEEE İnternational Conference On Automatic Face & Gesture Recognition (FG 2017)* (pp. 814-819). IEEE.

Guo, J., Lei, Z., Wan, J., Avots, E., Hajarolasvadi, N., Knyazev, B., Kuharenko, A., Junior, J. C. S. J., Baro, X., Demire, H., Escalera, S. Allik, J., & Anbarjafari, G. (2018). Dominant and complementary emotion recognition from still images of faces. *IEEE Access, 6,* 26391-26403.

Haamer, R. E., Rusadze, E., Lsi, I., Ahmed, T., Escalera, S., & Anbarjafari, G. (2017). Review on emotion recognition databases. *Hum. Robot Interact. Theor. Appl*, *3*, 39-63.

Heshmati, S., Sbarra, D. A., & Mason, A. E. (2017). The contemptuous separation: Facial expressions of emotion and breakups in young adulthood. *Personal Relationships*, *24*(2), 453-469.

Hu, P., Cai, D., Wang, S., Yao, A., & Chen, Y. (2017). Learning supervised scoring ensemble for emotion recog-nition in the wild. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction* (pp. 553-560).

Jiddah, S. M., & Yurtkan, K. (2023). Dominant and complementary emotion recognition using hybrid recurrent neural network. *Signal, Image and Video Processing*, *17*(7), 3415-3423.

Keltner, D., Sauter, D., Tracy, J., & Cowen, A. (2019). Emotional expression: Advances in basic emotion theory. *Journal of Nonverbal Behavior, 43*(2), 133-160.

Kulkarni, K., Corneanu, C. A., Ofodile, I., Escalera, S., Baro, X., Hyniewska, S., ... & Anbarjafari, G. (2018). Automatic recognition of facial displays of unfelt emotions. *IEEE Transactions on Affective Computing, 12*(2), 377-390.

Lazarus, R. S. (2006). *Stress and emotion: A new synthesis.* New York, NY: Springer.

Lerner, J. S., Dahl, R. E., Hariri, A. R., & Taylor, S. E. (2007). Facial expressions of emotion reveal neuroendocrine and cardiovascular stress responses. *Biological Psychiatry, 61*(2), 253-260.

Levi, G., & Hassner, T. (2015). Emotion recognition in the wild via convolutional neural networks and mapped binary patterns. *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction* (pp. 503-510).

Loob, C., Rasti, P., Lusi, I., Jacques, J. C., Baró, X., Escalera, S., ... & Anbarjafari, G. (2017). Dominant and comple-mentary multi-emotional facial expression recognition using c-support vector classification. In *12th International Conference on Automatic Face & Gesture Recognition (FG 2017)* (pp. 833-838). IEEE.

Lusi, I., Junior, J. C. J., Gorbova, J., Baró, X., Escalera, S., Demirel, H., ... & Anbarjafari, G. (2017). Joint challenge on dominant and complementary emotion recognition using micro emotion features and head-pose estimation: Databases. *International Conference on Automatic Face & Gesture Recognition (FG 2017)* (pp. 809-813). IEEE.

Martinez, B., & Valstar, M. F. (2016). Advances, challenges, and opportunities in automatic facial expression recognition. In *Advances in face detection and facial image analysis* (pp.63-100). Springer.

Nonis, F., Dagnes, N., Marcolin, F., & Vezzetti, E. (2019). 3D approaches and challenges in facial expression recognition algorithms—A literature review. *Applied Sciences, 9*(18), 3904.

Noroozi, F., Marjanovic, M., Njegus, A., Escalera, S., & Anbarjafari, G. (2017). Audio-visual emotion recognition in video clips. *IEEE Transactions on Affective Computing, 10*(1), 60-75.

Sajjad, M., Ullah, F. U. M., Ullah, M., Christodoulou, G., Cheikh, F. A., Hijji, M., & Rodrigues, J. J. (2023). A comprehensive survey on deep facial expression recognition: challenges, applications, and future guidelines. *Alexandria Engineering Journal, 68,* 817-840.

Schriber, R. A., Chung, J. M., Sorensen, K. S., & Robins, R. W. (2017). Dispositional contempt: A first look at the contemptuous person. *Journal of Personality and Social Psychology, 113*(2), 280.

Yu, Z., Liu, G., Liu, Q., & Deng, J. (2018). Spatio-temporal convolutional features with nested LSTM for facial expression recognition. *Neurocomputing, 317,* 50-57.

Zautra, A. (2006). *Emotions, stress, and health.* Oxford: Oxford University Press.

Zautra, A. J., Berkhof, J., & Nicolson, N. A. (2010). Changes in affect interrelations as a function of stressful events. *Cognition & Emotion, 16*(2), 309-318.

Zhang, J., Mei, X., Liu, H., Yuan, S., & Qian, T. (2019). Detecting negative emotional stress based on facial expression in real time. In *2019 IEEE 4th international conference on signal and image processing (ICSIP)* (pp. 430-434). IEEE.

Zhao, X., Liang, X., Liu, L., Li, T., Han, Y., Vasconcelos, N., & Yan, S. (2016). Peak-piloted deep network for facial expression recognition. In *European Conference on Computer Vision* (pp. 425-442). Cham: Springer.

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